POLICY BASED QOS MONITORING
Automated Learning Strategies for Policy Enhancement

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Abstract: A challenge of today's measurement architectures for QoS/SLA monitoring in heterogeneous network environment is enhanced intelligence in order to minimise measurements and derive automatically optimised measurement strategies for the network operators. Such optimisations can be done with different goals – avoid redundant measurements, sharing of measurements for different QoS monitoring goals and enhancement of measurement strategies considering QoS/SLA measurement requests. For automated optimisation of measurement strategies, QoS measurement policies are proposed whose parameters are adapted dynamically based on specified learning algorithms and rules. For the policy adaptation different kinds of learning can be used, as for instance reinforcement and supervised learning. The integration of the proposed policy based strategies into policy management architecture is discussed. A learning component collecting rules and algorithms for measurement policy adaptation is proposed which can be used by different tools of a policy management system. A graphical user interface (GUI) for a realistic policy based measurement scenario is discussed which aims to optimise the measurement strategies of the network operator.

1 INTRODUCTION

Advanced architectures for monitoring of QoS parameter and Service Level Agreement (SLAs) offer automated measurement facilities and techniques for data mining and analysis of measurement data. Examples for such architectures are CMToolset (Miloucheva et al., 1997), (Hofmann et al., 2001), INTERMON toolkit (Miloucheva, Aranda, Hetzerand Nassri,2004), (Miloucheva, Hetzer and Guitierres, 2004), (Miloucheva, Hetzerand Nassri, 2004), MoME architecture (Brandauer et al., 2007), (IST-MOME, see ref).
In such architectures measurement scenarios are used to achieve the specific requirements for data mining and analysis of measurement data dependencies, as for instance:

- Effect of inter-domain routing and BGP-4 protocol behaviour on QoS parameter values (see (Gutierrez et al, 2004)),
- Traffic and congestion impact on the QoS of applications (see (Miloucheva, Hetzer and Guitierres, 2004)),
- Data mining and dependency analysis (Miloucheva, Hetzerand Nassri, 2004),
- Anomaly detection (Gutierrez, Anzaloni and Müller, 2003),
- Support of proactive and reactive bandwidth planning (Hetzer et al., 2006),
- Optimisation of on-demand multimedia content delivery (Hetzer, Milouchevaand Jonas, 2006).

Although there are different approaches to integrate analysis and modelling facilities for different tasks into the QoS/SLA monitoring architectures there is still a challenge arising from redundant measurements performed with such tools.

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Even if the measurement goals are different (e.g. bandwidth planning, anomaly detection) it is possible that redundant measurements are performed whose results can be inferred from other requested measurements. This leads to significant load of the network infrastructure by needless measurement overhead.

To avoid this overhead additional facilities integrated in the QoS/SLA monitoring infrastructure are considered which are aimed to analyse the measurement scenarios based on their descriptions and the dependencies of their results. Such "intelligent" facility can be designed to optimise the QoS measurements for a given period of time considering the requirements of the different users and applications, for which measurements are done. By this, avoidance of redundant measurements and sharing of measurement results for different tasks can be achieved.

In this paper, in order to support the automatic minimisation of measurements and sharing of measurement results for the requested QoS monitoring tasks, policies and learning algorithms are used. Policies specify which measurements have to be done for the different users and applications. Learning algorithms analyse the established policies and corresponding measurement scenarios with the goal to minimise the measurement overhead and share measurement results.

Design considerations of the policy oriented QoS monitoring architecture allowing minimisation of measurements are discussed in this paper.

The paper is organised as follows.

Section 2 gives a brief overview of QoS/SLA monitoring architectures with integrated data mining functions. The general approach of learning for optimisation of measurement scenario suite and their parameters is discussed in section 3. In section 4 the design of a learning component in a policy based measurement system is presented. Section 5 describes a scenario based on measurement policies for optimisation of measurement strategies.

2 POLICY BASED QOS/SLA MONITORING

Advanced QoS/SLA monitoring architectures are aimed at automation of measurements and their analysis for specific tasks. Example of such architectures are CMToolser (Miloucheva et al., 1997), (Hofmann et al., 2001), INTERMON (Miloucheva, Aranda, Hetzerand Nassri,2004),(Miloucheva, Hetzer and Guitierres, 2004), (Miloucheva, Hetzerand Nassri, 2004), MoMe (Brandauer et al., 2007),(IST-MOME, see ref), Skitter (CAIDA's Skitter project web page), Surveyor (Kalidindi, 1999), SPAND (Seshan et al., 1997).

QoS/SLA monitoring architectures can be based on active or passive measurement scenarios, which are stored in appropriate measurement data repositories for further processing.

A raising problem of such architectures is the large volume of measurement data and the great measurement overhead, which consumes resources of the network infrastructure.

One approach to solve the problem is to use Very Large scale Data Base (VLDB) design of measurement data repositories occupying magnetic storage in the terabyte range and containing billions of table rows and to improve the efficiency of the operations concerning the measurement data base (Gray, 2004).

Another approach is proposed in this paper which is based on QoS monitoring whose measurements are specified using policies (goals) on different refinement levels.

Examples for policy actions, which are invoked when specific events or conditions take place, are:

- VoIP Quality measurement between two end-systems;
- Traffic load monitoring at a specific router, when the router is considered for traffic forwarding;
- Monitor anomalies of routing path.

Policies are defined by condition and actions sequences. In the case of policy based QoS/SLA monitoring, the measurement policies are described based on actions including measurement scenarios.

P: <condition> <action>

Policies can be specified using appropriate user-friendly Graphical User Interfaces (GUIs) similar to the GUIs of the available measurement architectures. The QoS/SLA monitoring GUI translates the input parameters into policy descriptions, which can be more effectively processed based on the "condition, action" relationships.

Learning algorithms can be integrated in the policy monitoring architecture in order to improve the policies and avoid repeated measurements, as well as to support sharing of measurement data.

The policy based QoS/SLA monitoring architecture is shown in figure 1:

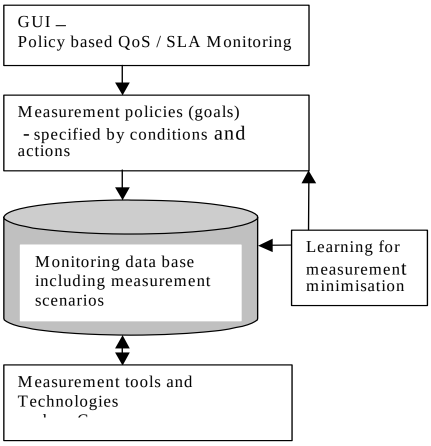

Figure 1: Policy based QoS/ SLA monitoring.

3 MEASUREMENT POLICIES AND THEIR ADAPTATION

The measurement policy model is derived from the IETF policy framework and was enhanced with concepts for automated learning and adaptation.

3.1 QoS Measurement Policies

Network management policies are considered as rules to administer, manage and control access to the network resources by applications and users (see RFC 3198 (Westerinen et al., 2001)). Policies express business goals and consist of condition and actions for management of parameters of the networks (Moore et al., 2001), (Moore, 2003), (Sahita et al., 2003).
IETF QoS management is addressed by the QoS Policy Information Model (QPIM) (Snir et al., 2003). QoS policies are mainly focussed on management of IntServ and DiffServ resource allocation by the network administrator. IETF also focussed on management of network device QoS data path mechanisms using policies (Moore et al, 2004).
A new type of QoS management policies aimed at management of measurement strategies, is considered in this paper.
QoS measurement policies are aimed at configuring and/or adapting of QoS/SLA measurements in heterogeneous network environments depending on events, network capabilities and preferences provided by the different actors (i.e. users, service providers and/or network operators).
Each network provider has QoS measurement policies to measure and report the quality of the network depending on the QoS/SLA. Measurement policies can be used to select appropriate measurements or tasks, such as proactive QoS planning, QoS problem and anomaly detection.
The proposed measurement policies introduce some new aspects considering current IETF framework. Such are:

1. The focus of the policy actions is configuration of measurement scenarios and corresponding measurement tools. This includes the control of parameters of measurement scenarios, as well as the set of measurement scenarios required to provide a measurement action.
2. Measurement policies can be defined for different kind of policy actors (i.e. users, service providers and network operators). The relationships between the policy actors can be used to infer adaptation of policy parameters.

Measurement policies can be specified in a user-oriented language as “high level” goals which are translated into executable procedures and corresponding data structures.

P_{meas} : <meas_condition> <measurement_action>

<meas_condition> : < netw_event> I < actor_preference>

<netw_event> : <congestion> I <failure> I <anomaly> I <learning_event>

<meas_action> : “set” <meas_scen> I “ref” <meas_scen> I “update” <meas_scen>

The definition shows the structure of measurement policy conditions (<meas_condition>) and actions (<meas_action>).

The measurement action can be:
- Establishment of new measurement scenario (“set”<meas_scenario>),
- Reference to existing measurement scenario (“ref” <meas_scenario>) and
- Update of parameter of measurement scenarios (“update” <meas_scenario>).

Measurement scenarios can be represented abstractly by the following expressions:

<meas_scenario>:
<tool><meas_par><meas_result><meas_topoligy><time_spec><meas_param>

The expression gives the usual configuration parameters of a measurement scenario:

- Tools (<tool>) used for measurements and their installation parameters, which can depend on the network;
- Measured application QoS parameters (<meas_par>), which are measured, as for instance delay, traffic, response time;
- Measurement result (<meas_result>) is specified by the required granularity of the measurements and other parameters;
- Measurement topology (<meas_topology>) specifies the network elements between the measurements are performed;
- Scenario execution time specifies the frequency and the time interval, in which the scenario is executed (<time_spec>).

Analysing the dependencies of the measurement scenario parameters and changing appropriately specific parameters of the measurement scenario, the measurements performed by the QoS/SLA architecture can be minimised.

3.2 Learning for Measurement Policy Optimisation

The policies and their corresponding measurement scenarios can be adapted dynamically to support more efficient QoS/SLA of applications with monitoring data and to detect more efficiently problems in the heterogeneous infrastructure.
Parameters of the measurement scenarios can be adapted dynamically using learning techniques. The learning algorithms can be of different kinds of complexity and design using theoretical approaches discussed in the state-of-the art (Sutton 1998), (Bertsekas et al., 1996).

Supervised and reinforcement learning can be used for improvement of measurement policies:

- Reinforcement learning (Sutton 1998) is a theoretical approach to study dynamically the impact of the environment and improve automatically the used policies. Reinforcement learning algorithms are based on knowledge of environment. There are different reinforcement learning technique, such as Q-learning (Watkins et al., 1992), informed reinforcement learning (Croonenborghs et al., 2004) and relational reinforcement learning (Driessens et al., 2002).

- The supervised learning assumes a “teacher signal” that explicitly tells the correct output for every input pattern (Urbancic, 1996). The main task is focussed on the mapping of input patterns to target output values.

Considering measurement policies, reinforcement learning strategies can be used for example to automate the search for the most appropriate measurements, thus reducing measurement overhead. Reinforcement learning algorithms, which use knowledge from the networking environment and operational events to update the parameters of the measurement policy parameters, can be used to:

- Adapt the measurement topology (meas_topology) of policies based on the actual network topology;
- Change measurement parameters (meas_par) based on congestion, traffic changes and other events derived from environment.

The supervised learning algorithms can be used basically to adapt parameters of measurement policies considering dependencies of the actors of policies.
The network operator checks the requested measurements defined in the policies of service providers and end-users and changes their parameters using a simple learning algorithm.
Considering the hierarchical actor dependencies, supervised learning can also be based on processing and adaptation of policies from measurement parameters of other policies
In order to improve the policy specifications, learning can be done in top-down and bottom-up manner considering the hierarchical relationships of the policy actors. Hierarchical relationships of policies can be defined based on the dependencies of the policy actors. For instance, network providers can be interested in monitoring of different QoS characteristics, such as QoS parameter, anomalies, traffic measurements, route path quality and other (Miloucheva, Aranda, Hetzerand Nassri,2004). For the specification of monitoring and measurement tasks, ontology can be used, which allow to share and access the knowledge about measured QoS by the different policy actors.
An example is given in figure 2, which shows how the measurement policies of different actors can be improved in top-down and bottom-up manner using supervised learning methods.

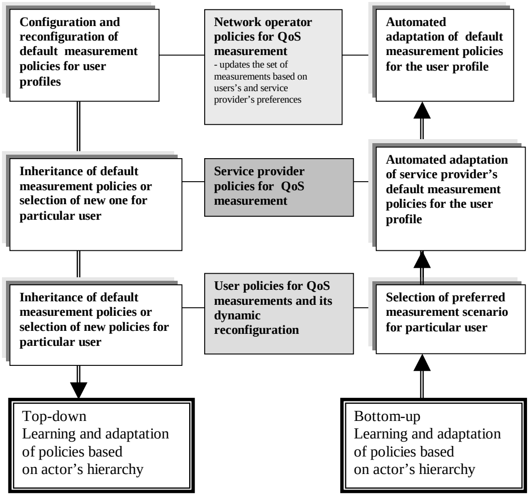

Figure 2: Learning approaches for enhancement of measurement policy.

In the bottom-up learning approach, the network operator checks the requested measurements defined in the policies of the service providers and end-users and adapts the parameters of his own measurement policies in order to avoid measurements, which are not requested by the policies of the other actors.

In the top-down learning approach, the end users and service provider can also automatically adapt their policies considering the goals of the network operator.

4 LEARNING COMPONENT

For automatic policy adaptation a learning component including different kinds of learning algorithms can be integrated in the policy management architectures.

The learning component can be considered as a collection of learning algorithms, which are used by different functional modules of a policy management system. This allows enhanced management of the adaptations, which are done based on different kinds of learning in the system.

Currently, the policy based management framework defined by the IETF (Westerinen et al., 2001), (Moore et al., 2001), (Moore, 2003), (Sahita et al., 2003), (Snir et al., 2003), is based on interaction of Policy Management Application (PMA), Policy repository – containing the policies, Policy Enforcement Point (PEP) -and Policy Decision Point (PDP).

The integration of the learning component in the IETF policy management architecture is shown in figure 3:

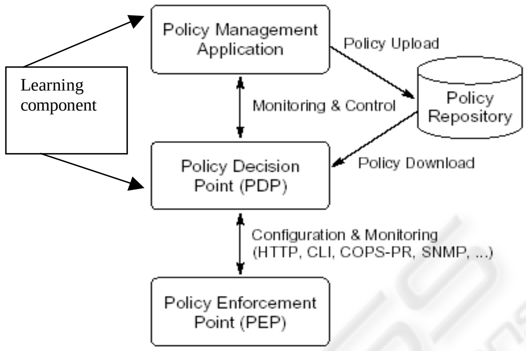

Figure 3: IETF policy management architecture enhanced with learning component.

In the enhanced policy management architecture, the learning component is used to integrate learning algorithms supporting different levels of the architecture. This means that learning algorithms, contained in a common learning component, can be used during the Policy Configuration phase by the Policy Management Application and during the Policy Decision phase by the PDP.

This design supports:

- Enhanced data mining to infer policy changes based on learning;
- Reusability of learning algorithms for different tasks, because the learning algorithms are contained in a common package of modules;
- Common functions for access and execution of learning procedures used by the different system components (Policy Management Interfaces and Policy Decision Point).

5 SCENARIOS AND INTERFACE FOR MEASUREMENT POLICY

Let's consider different policy actors, such as user, service provider and network operators, which require QoS measurements in heterogeneous environment using policies. These policy actors can define their measurement strategies for a heterogeneous environment using the interfaces for predefined measurement policy configuration integrated in the Application Preference Manager.

Such an interface of a policy actor (i.e. GUI of a policy management application), proposed in the framework of NETQOS project, is given in figure 4:

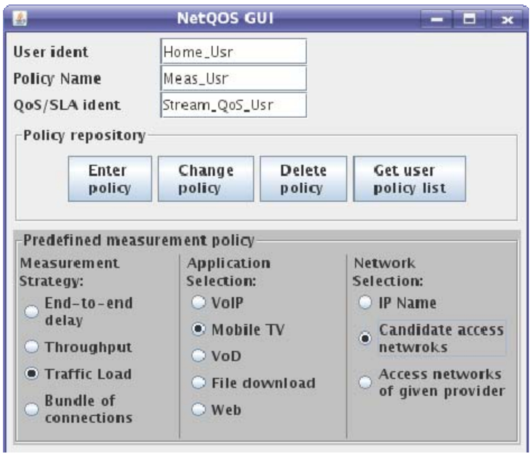

Figure 4: Interface for configuration of measurement policies for heterogeneous networks.

The configuration of a measurement policy by a policy actor is based on specification of measurement strategy type, application type and the access networks, for which the measurements are performed. The measurement strategy can target, for instance, end-to-end delay and depends on the application type.

Using the proposed interface, the end-users and service providers can specify their measurement requests to the NETQOS monitoring and measurement subsystem (Brandauer et al., 2007) as policies, which are stored in the repository. Learning algorithms can be used to analyse the set of measurement specifications and derive the most appropriate measurement suite for particular access networks and end-systems. Based on the optimised measurement scenarios, the measurement policies of the network providers can be improved.

This optimisation allows the network operator to avoid redundant measurements although considering requests from users and service providers.

6 CONCLUSIONS

This paper discusses an approach for integration of measurement policies and learning algorithms in existing QoS/SLA monitoring architectures. The proposed policy based measurement reduces measurement overhead in the network by detecting redundant measurements and optimising measurement strategies of network administrators.

Further work is aimed at design and integration of QoS measurement ontology, which enables the knowledge sharing, modelling and presentation using standardised techniques, as well as formal analysis of the dependencies between measurements.

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